Spatial Epidemiology of Police Use of Force:
Identifying Geographic Patterns and Correlates in Seattle

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Abstract

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Despite growing evidence of social and racial disparities in policing outcomes, relatively little is known about the geographic distribution of police use of force (UOF) within cities or the neighborhood characteristics associated with elevated UOF rates. This study examined the spatial distribution of police UOF across Seattle census tracts and assessed the association between neighborhood socioeconomic disadvantage and UOF rates.

Police UOF incident data from the Seattle Police Department covered 177 Seattle census tracts for the years 2020-2024. Census tract-level demographic and socioeconomic data came from the American Community Survey and the City of Seattle Race and Social Equity Index. We assessed spatial clustering using Global Moran's I, Local Indicators of Spatial Association (LISA), and Getis-Ord Gi* hotspot analysis. We estimated associations between neighborhood socioeconomic disadvantage and UOF rates using Poisson quasi-likelihood regression models with robust standard errors and a log population offset. We assessed residual spatial

autocorrelation using Moran's I, and conducted a post hoc spatial lag model to examine spatial dependence.

Police UOF rates demonstrated significant positive spatial autocorrelation across Seattle census tracts (Moran's I = 0.31, $p < 0.001$), with hotspots concentrated in central and southern Seattle. In fully adjusted regression models, greater neighborhood socioeconomic disadvantage was associated with higher UOF rates (IRR = 1.15, 95% CI: 1.00, 1.31). Significant spatial autocorrelation remained in the model residuals (Moran's I = 0.259, $p < 0.001$), suggesting the presence of additional spatially structured factors. In a post hoc spatial lag model, the association between socioeconomic disadvantage and UOF attenuated (IRR = 1.04, 95% CI: 0.91, 1.17), while neighboring tract UOF rates were positively associated with local UOF rates (IRR = 1.03 per 10-unit increase, 95% CI: 1.02, 1.04).

Introduction

Police use of force (UOF) represents a consequential policing outcome that occurs unevenly across populations and communities in the United States. Although public discourse often focuses on the immediate physical harms associated with police UOF, including injury or death, the health impacts of policing may extend beyond individual encounters and contribute to broader patterns of psychological distress and community-level harm. Exposure to police violence and aggressive policing practices has contributed to psychological distress, anxiety, depression, trauma symptoms, reduced trust in institutions, and chronic stress among both directly affected individuals and surrounding communities (DeVylder et al., 2022; Webb & Kline, 2025; Ribeiro, 2018). These effects may accumulate over time and contribute to broader patterns of social inequity, community disinvestment, and population-level health disparities.

Recent public health literature has conceptualized policing itself as a social determinant of health and police violence as a population-level exposure shaped by structural and neighborhood conditions that can impact community health outcomes and reinforce existing social inequities (DeVylder et al., 2022; Webb & Kline, 2025; Lee et al., 2023). Simckes and colleagues proposed a conceptual model describing how policing exposures operate through direct and indirect pathways to influence health at individual, community, and systems levels (Simckes et al., 2021). Their framework emphasizes that policing exposures extend beyond direct encounters with law enforcement and include indirect or vicarious experiences occurring through social networks, community awareness, media exposure, and neighborhood surveillance environments. The model further highlights how contextual factors, including neighborhood socioeconomic conditions, organizational policing practices, historical inequities, and broader policy environments, shape both exposure to policing and its downstream health consequences. Within this framework, researchers can understand policing as a structurally patterned exposure with implications for population health, community wellbeing, and health equity.

This conceptualization is particularly relevant to police UOF, which does not occur randomly across populations or geographic space. A substantial body of research has documented persistent racial and socioeconomic disparities in police contact and UOF in the United States. Black, Indigenous, and other racially marginalized populations experience disproportionately high rates of police force relative to White populations, even after accounting for differences in situational or incident-level characteristics (Hoekstra & Sloan, 2022). These inequities reflect broader structural and institutional processes, including racial segregation, concentrated poverty, and differential surveillance and enforcement practices across communities (Hoekstra & Sloan, 2022; Allen, 2024).

Neighborhood context may play a particularly important role in shaping exposure to police UOF. Socioeconomically disadvantaged neighborhoods experience higher levels of police presence, enforcement activity, and investigative stops, thereby increasing cumulative exposure to policing practices (Hoekstra & Sloan, 2022). These patterns may persist independent of crime rates and may reflect broader institutional responses to concentrated disadvantage and racialized neighborhood conditions. In addition, neighborhood characteristics such as population density, land use, transportation infrastructure, and demographic composition may influence where police interactions occur and how enforcement resources are distributed across space (Matthews et al., 2010). The literature supports conceptualizing police UOF as a geographically and structurally patterned phenomenon shaped by social and neighborhood contexts.

Spatial epidemiology offers a useful framework for examining the relationship between neighborhood context and police UOF by recognizing that population health outcomes are often geographically patterned and shaped by contextual neighborhood conditions (Ribeiro, 2018). Spatial analysis allows researchers to identify geographic clustering, assess neighborhood-level variation, and evaluate whether outcomes are concentrated within particular areas. Prior research has demonstrated that crime and policing outcomes often exhibit strong spatial patterning, with neighboring areas tending to share similar levels of enforcement activity and rates of criminal legal system involvement among residents (Crawford, 2018; Kikuchi, 2010). Research conducted in Seattle has shown that characteristics of the built environment, including housing density, land use mix, and transit accessibility, contribute to geographic variation in crime across neighborhoods (Matthews et al., 2010). Despite growing recognition that place and geography influence policing outcomes, there remains limited application of spatial epidemiologic methods to the study of police UOF.

Seattle represents a particularly informative setting in which to examine the spatial distribution of police UOF. The city has experienced substantial demographic change, rapid urban development, persistent racial and socioeconomic segregation, and ongoing gentrification, all of which contribute to heterogeneous neighborhood environments. In addition, the Seattle Police Department (SPD) operated under a federal consent decree from 2012 through 2025 following a United States Department of Justice investigation that identified patterns of excessive force and evidence of biased policing (United States Attorney, 2012). The consent decree mandated reforms related to training, accountability, and oversight and substantially shaped policing practices during much of the study period covered by this analysis. This regulatory and political context is important for interpreting contemporary patterns of police UOF within Seattle neighborhoods.

Despite increasing public and scholarly attention to police violence and policing inequities, important gaps remain in the literature. First, few studies have examined police UOF using explicitly spatial epidemiologic approaches capable of identifying geographic clustering and spatial dependence. Second, while neighborhood socioeconomic disadvantage has been linked to policing exposure nationally, limited research has evaluated these associations at the local level using neighborhood-scale spatial analysis. Third, no study has systematically examined the spatial distribution of police UOF across Seattle census tracts or assessed the extent to which neighborhood structural characteristics are associated with variation in UOF rates across the city.

The purpose of this study was to examine the spatial distribution of police UOF across Seattle census tracts and assess associations between neighborhood socioeconomic disadvantage and UOF rates using spatial epidemiologic methods. Specifically, this study aimed to: (1) characterize the geographic distribution and spatial clustering of police UOF incidents across Seattle census tracts, and (2) examine associations between neighborhood socioeconomic disadvantage and census tract-level UOF rates. We hypothesized that police UOF would demonstrate significant geographic clustering and that neighborhoods with greater socioeconomic disadvantage would experience higher rates of UOF. By integrating spatial analytic methods with neighborhood-level regression modeling, this study contributes to the growing literature examining police UOF as a geographically patterned phenomenon shaped by neighborhood and structural conditions. Additionally, this study provides a foundation for future research investigating how spatial variation in policing may intersect with broader questions of health equity, community safety, and violence prevention. Throughout this manuscript, “use of force” refers to the terminology used in the Seattle Police Department dataset from which the study outcome measurement was derived. Related literature may also conceptualize or refer to these events as police violence.

Methods

This study employed a cross-sectional ecological design to examine the spatial distribution of police UOF and its association with neighborhood socioeconomic disadvantage across Seattle census tracts between 2020 and 2024. Data management and analysis were conducted using R (version 4.5.0). Multiple data sources were integrated at the census tract level to construct the analytic dataset, including police UOF incident data, American Community Survey (ACS) estimates, and neighborhood-level socioeconomic indicators from the City of Seattle Race and Social Equity (RSE) Index. The University of Washington Institutional Review Board determined that this project did not meet the federal definition of human subjects research and therefore did not require IRB review or approval.

Police UOF incident data came from the Seattle Police Department. Although publicly available, a data sharing agreement with SPD was required, and obtained, to access geographic coordinates of UOF incidents. The analytic dataset included incident-level records occurring between 2020 and 2024 and contained information on incident date and time, geographic coordinates, force level, and limited contextual descriptors. We excluded one tract with missing or invalid geographic coordinates, as well as one tract falling outside Seattle census tract boundaries prior to spatial aggregation and analysis (n=2).

Census tract-level population estimates came from the 2016-2020 five-year American Community Survey using the tidycensus package. This time period was selected to align with the City of Seattle Race and Social Equity Index, which is based on the same ACS estimates, to ensure comparability across data sources. We extracted and retained total population counts by census tract Federal Information Processing Standards (FIPS) code (GEOID). Census tract boundaries came from 2020 TIGER/Line shapefiles using the tigris package.

Neighborhood-level demographic and socioeconomic variables came from the City of Seattle's Race and Social Equity Index (Diana Canzoneri et al., 2023). The primary exposure, socioeconomic disadvantage, consisted of a composite index calculated as the average of two equally weighted indicators: the proportion of residents with income below 200% of the federal poverty level and the proportion of adults without a bachelor's degree, with higher values indicating greater disadvantage. We selected this index because it captures key dimensions of neighborhood socioeconomic conditions while excluding race and ethnic composition, allowing neighborhood disadvantage and racial composition to be examined separately within regression models.

Additional tract-level covariates included the proportion of male residents, residents aged 18-34 years, and residents identifying as Black, Indigenous, or People of Color, excluding Asian individuals. We selected covariates a priori based on a conceptual causal framework (Supplemental Figure 1) and prior policing and criminology literature demonstrating that younger populations, males, and racially marginalized populations experience disproportionately high rates of police contact and UOF. Because these demographic characteristics are also associated with neighborhood socioeconomic disadvantage, they were conceptualized as potential confounders of the association between neighborhood disadvantage and UOF. Adjustment was therefore performed to assess whether any observed association between socioeconomic disadvantage and UOF persisted after accounting for differences in neighborhood demographic composition.

We merged all datasets using census tract geographic identifiers. We aggregated UOF counts to the census tract level and rates were calculated per 10,000 residents. We calculated population density as total population per square mile and log-transformed to reduce skewness. We excluded census tracts with near-zero population, resulting in a final analytic sample of 177 census tracts (n=1).

Spatial and Statistical Analysis

All analyses were specified a priori, with the exception of the spatial lag model, which was added post hoc after evidence of residual spatial autocorrelation was identified.

Spatial analyses assessed whether census tract-level police UOF rates were geographically clustered across Seattle and to examine their associations with socioeconomic disadvantage. We defined census tract adjacency using queen contiguity, such that tracts sharing either a border or vertex were considered neighbors. We then constructed row-standardized spatial weights. Global Moran's I assessed overall spatial autocorrelation in UOF rates across census tracts. Local Indicators of Spatial Association (LISA) identified localized clusters and spatial outliers, including high-high clusters and low-high outliers. We additionally conducted Getis-Ord Gi* hotspot analysis to identify statistically significant concentrations of elevated UOF rates. We classified hotspots and cold spots twice, once using $p < 0.05$ as a z-score threshold and once using $p < 0.01$.

Aspatial regression models estimated associations between neighborhood socioeconomic disadvantage and UOF rates. Because the outcome represented counts of UOF incidents by census tract, models included a log population offset to estimate incident rate ratios (IRRs). The primary exposure was socioeconomic disadvantage, scaled so that estimates represented the association per 0.1-unit increase (10%) in the index (range: 0-1). The unadjusted model (Model 1) was considered the primary estimate because it quantifies the overall disparity in UOF rates across neighborhoods with differing levels of socioeconomic disadvantage. Model 2 adjusted for population density, and Model 3 additionally adjusted for neighborhood demographic composition (percent male, percent aged 18-34 years, and percent BIPOC excluding Asian residents). These adjusted models were specified as sensitivity analyses to evaluate whether associations observed in the primary model persisted after accounting for demographic and structural neighborhood characteristics associated with policing exposure.

A negative binomial was originally planned because UOF counts were highly overdispersed. However, the negative binomial model did not converge, including after attempts to address influential extreme values. Therefore, we used Poisson quasi-likelihood models with robust standard errors to estimate IRRs and 95% confidence intervals while accounting for overdispersion and improving statistical inference.

We mapped and examined Pearson residuals from the fully adjusted model to assess spatial patterns in model fit and identify areas where observed UOF counts systematically differed from model-expected values. We then calculated Global Moran's I for the residuals using queen contiguity weights to determine whether residual spatial autocorrelation remained after adjustment for model covariates.

As a post hoc analysis, we added a spatially lagged UOF rate to the fully adjusted model determined a priori. The spatial lag term represents the average UOF rate in neighboring census tracts, based on the previously defined spatial weights. This model assessed whether the association between socioeconomic disadvantage and UOF rates persisted after accounting for spatial dependence in nearby areas.

Results

Descriptive Characteristics of Census Tracts

A total of 177 census tracts within Seattle were included in the analysis. Across the five-year study period, the mean number of police UOF incidents per tract was 37.34 (SD: 61.08), corresponding to a mean rate of 109.01 incidents per 10,000 residents (SD: 231.81) (Table 1). The median UOF rate was 42.03 per 10,000 residents (IQR: 20.88, 101.34), indicating a right-skewed distribution of UOF rates across census tracts.

Density plots of UOF rates stratified by neighborhood socioeconomic disadvantage quartile demonstrated a progressive rightward shift in the distribution as disadvantage increased (Supplemental Figure 1). Tracts in the highest disadvantage quartile (Q4) generally exhibited higher UOF rates and greater dispersion than tracts in lower disadvantage quartiles. The distribution for Q4 also displayed a longer right tail, suggesting that the highest UOF rates were concentrated in the most socioeconomically disadvantaged neighborhoods.

Consistent with these patterns, UOF rates exhibited a clear socioeconomic gradient across quartiles of neighborhood socioeconomic disadvantage. Census tracts in Q4 had the highest mean UOF rates (179.09 per 10,000 residents, SD: 327.14), compared with 30.83 per 10,000 residents (SD: 34.12) among tracts in the lowest disadvantage quartile (Q1). Median UOF rates similarly increased across quartiles of neighborhood socioeconomic disadvantage (Table 1).

Neighborhood demographic and structural characteristics differed across quartiles. Tracts with higher socioeconomic disadvantage had higher proportions of Black and Hispanic residents and lower proportions of White residents. Population density and age structure showed only modest differences across quartiles, while the proportion of residents aged 18-34 increased with neighborhood disadvantage (Table 1).

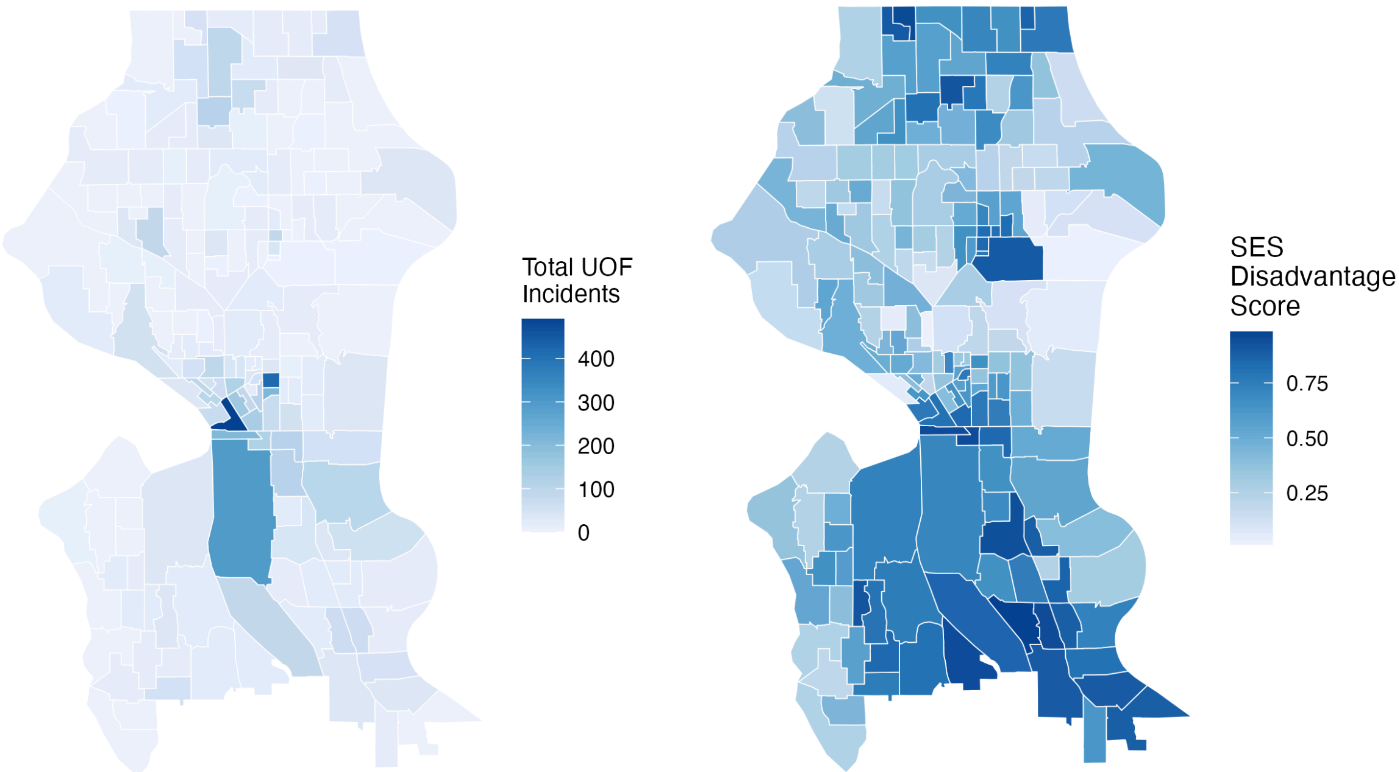
Table 1: Characteristics of Seattle Census Tracts Overall and by Quartiles of Socioeconomic Disadvantage, 2020-2024

Characteristic	Overall	Q1 Lowest Disadvantage	Q2	Q3	Q4 Highest Disadvantage
Number of census tracts, n	177	45	44	44	44
UOF count per tract*, mean (SD)	37.34 (61.08)	12.29 (11.36)	37.16 (68.3)	42.68 (56.79)	57.82 (78.32)
UOF rate per 10,000 residents, mean (SD)	109.01 (231.81)	30.83 (34.12)	105.63 (243)	122.26 (202.65)	179.09 (327.14)
Median (IQR) UOF rate	42.03 (20.88, 101.34)	25.27 (13.01, 35.22)	36.52 (20.34, 80.42)	48.85 (32.46, 123.54)	75 (50.65, 178.24)
Socioeconomic Disadvantage Index†, mean (SD)	**0.5 (0.26)**	**0.18 (0.07)**	**0.39 (0.07)**	**0.6 (0.06)**	**0.84 (0.07)**
Total population‡, mean (SD)	4187.41 (1178.46)	4287.07 (1331.41)	4253.45 (1057.54)	4038.86 (1159.77)	4167.98 (1170.08)
Population density‡ (per sq mile), mean (SD)	15861.21 (14994.16)	10996.69 (6828.19)	16314.22 (13368.42)	18800.6 (16367.87)	17443.91 (19735.86)
% under 18 years old‡, mean (SD)	13.7 (7.65)	16.83 (7.2)	12.74 (6.77)	11.37 (7.22)	13.81 (8.48)
% age 18-34 years old‡, mean (SD)	36.74 (19.02)	28.68 (17.03)	38.1 (16.16)	40.67 (17.71)	39.7 (22.67)

% age 65+ years old‡, mean (SD)	12.26 (6.22)	13.26 (5.75)	11.51 (6.2)	11.53 (5.74)	12.73 (7.11)
% male‡, mean (SD)	50.85 (5.39)	49.43 (3.93)	50.26 (5.39)	52.8 (5.11)	50.94 (6.46)
% Black residents‡, mean (SD)	6.65 (8.45)	1.63 (1.86)	3.74 (4.06)	6.42 (4.94)	14.93 (11.94)
% Hispanic residents‡, mean (SD)	6.99 (4.13)	4.99 (2.72)	6.04 (2.87)	7.15 (3.38)	9.82 (5.42)
% Asian residents‡, mean (SD)	16.75 (11.92)	12.43 (8.81)	13.13 (9)	17.74 (11.65)	23.8 (14.16)
% White residents‡, mean (SD)	62.42 (17.93)	75.46 (9.82)	69.34 (11.59)	61.53 (14.58)	43.06 (16.08)
% American Indian/Alaska Native residents‡, mean (SD)	0.42 (0.87)	0.15 (0.29)	0.33 (0.91)	0.46 (1)	0.75 (1)
% Other or multiracial residents‡, mean (SD)	0.61 (1.08)	0.44 (0.73)	0.54 (1.14)	0.62 (1.03)	0.84 (1.32)

*Source: Seattle Police Department. (2026)
†Source: City of Seattle. (2026). Racial and Social Equity Composite Index.
‡Source: United States Census Bureau. (2026). 2020-2024 American Community Survey.
Census tract-level characteristics for Seattle, Washington (n = 177), summarized overall and by quartiles of the City of Seattle Socioeconomic Disadvantage Index. Values are presented as mean (standard deviation) unless otherwise specified. Police use of force (UOF) rates are expressed per 10,000 residents. The socioeconomic disadvantage index ranges from 0 to 1, with higher values indicating greater disadvantage. Quartiles were defined based on the distribution of the index across census tracts.

Figure 1. Geographic Distribution of Police Use of Force Incidents and Neighborhood Socioeconomic Disadvantage Across Seattle Census Tracts, 2020-2024.



Total police use of force incidents aggregated across the study period. Census tracts categorized into quartiles of neighborhood socioeconomic disadvantage, with higher scores indicating greater disadvantage.

Aim 1: Spatial Distribution and Clustering of Police Use of Force

Global Spatial Autocorrelation

Global Moran's I indicated statistically significant positive spatial autocorrelation in census tract-level UOF rates ($I = 0.31$, $p < 0.001$), suggesting that tracts with similar UOF rates cluster geographically rather than distribute randomly across Seattle.

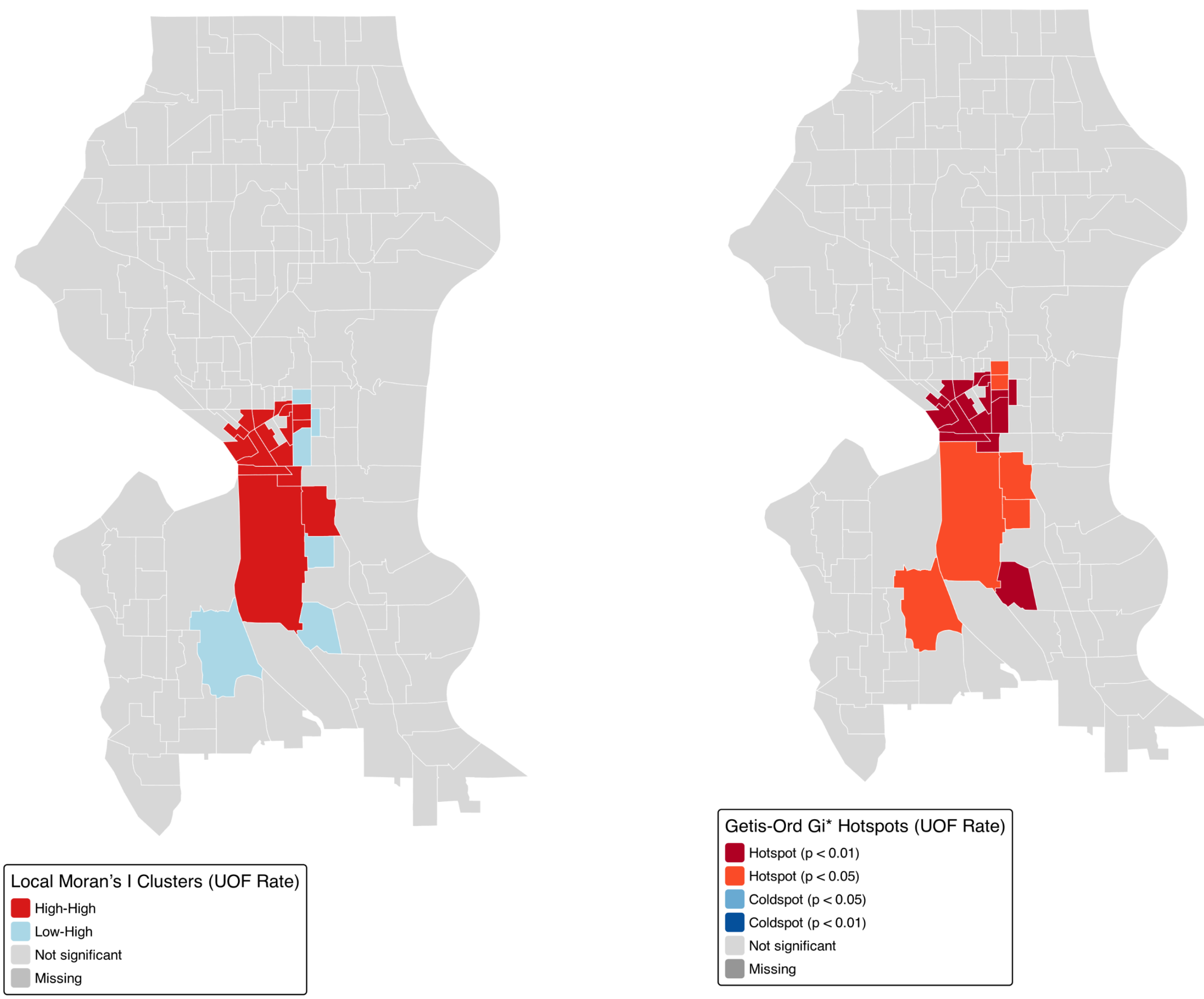
Local Spatial Clustering (LISA)

Local Moran's I analysis (also known as local spatial clustering, LISA) identified localized clusters of elevated UOF rates. A total of 16 census tracts formed high-high clusters, representing areas with high UOF rates surrounded by neighboring tracts with similarly high rates. These clusters occurred primarily in central and southern Seattle.

No low-low clusters emerged, indicating an absence of large contiguous areas with consistently low UOF rates. Six tracts functioned as low-high spatial outliers, representing tracts with relatively lower UOF rates located adjacent to higher-rate areas. The majority of tracts (n = 155) did not reach statistical significance, indicating that clustering was localized rather than widespread (Figure 2).

Figure 2. Spatial Clustering and Hotspots of Police Use of Force Across Seattle Census Tracts, 2020-2024. (A) Local Indicators of Spatial Association (LISA). (B) Getis-Ord Gi* Hotspot Analysis.

A. LISA map ***B. Getis-Ord Gi* map***



(A) Local Moran's I (LISA) analysis identifying spatial clustering of census tract–level police use of force (UOF) rates. High-high clusters represent tracts with high UOF rates surrounded by neighboring tracts with similarly high rates, while Low-high outliers represent lower-rate tracts adjacent to higher-rate tracts. (B) Getis-Ord Gi* hotspot analysis identifying spatial clusters of elevated UOF rates. Statistical significance was assessed using permutation testing. LISA clusters are shown for $p < 0.05$, and Gi* hotspots are shown for $p < 0.05$ and $p < 0.01$. Tracts not meeting significance thresholds are classified as not significant. No statistically significant coldspots were identified.

Hotspot Analysis (Getis-Ord Gi*)

Getis-Ord Gi* analysis identified 22 census tracts as statistically significant hotspots of UOF, including 16 tracts at $p < 0.01$ and 6 tracts at $0.01 < p < 0.05$. These hotspots occurred primarily in central and southern Seattle. Hotspots identified at $p < 0.001$ reflect stronger evidence of non-random spatial clustering than those identified at $p < 0.05$.

No statistically significant coldspots emerged. Several census tracts identified as high-high clusters in the LISA analysis also appeared as statistically significant hotspots in the Getis-Ord Gi* analysis, indicating consistent evidence of elevated local spatial clustering across methods. However, some tracts identified as low-high spatial outliers in the LISA analysis also appeared as as Gi* hotspots. This reflects differences in how the two methods characterize spatial structure, with LISA identifying tract-level relationships relative to immediate neighbors and Gi* identifying broader concentrations or elevated values across surrounding areas (Figure 2).

Aim 2: Association Between Socioeconomic Disadvantage and Police Use of Force

Regression Results

Across the three aspatial regression models, higher neighborhood socioeconomic disadvantage was associated with higher rates of police UOF (Table 2). In the unadjusted model, a 0.1-unit increase in the socioeconomic disadvantage index was associated with a 19% higher rate of UOF (IRR = 1.19, 95% CI: 1.09, 1.30), indicating substantial disparities in UOF rates across neighborhoods with differing levels of disadvantage. Adjustment for population density produced nearly identical estimates (IRR = 1.19, 95% CI: 1.09, 1.30). After additionally accounting for neighborhood demographic composition, the association attenuated modestly but remained positive (IRR = 1.15, 95% CI: 1.00, 1.31). The relative stability of estimates across models suggests that differences in neighborhood demographic composition did not fully explain the association between neighborhood socioeconomic disadvantage and UOF.

Table 2: Association Between Socioeconomic Disadvantage and Police Use of Force Rates in Seattle Census Tracts, 2020-2024

Variable	Model 1 Unadjusted IRR (95% CI)	Model 2 + Population Density IRR (95% CI)	Model 3 Fully Adjusted IRR (95% CI)	Model 4 Spatial Lag Sensitivity Analysis IRR (95% CI)
Socioeconomic disadvantage (per 0.1-unit increase)	1.19 (1.09, 1.30)	1.19 (1.09, 1.30)	1.15 (1.00, 1.31)	1.04 (0.92, 1.17)
Spatial lag of UOF rate (per 10-unit increase)	–	–	–	1.03 (1.02, 1.04)

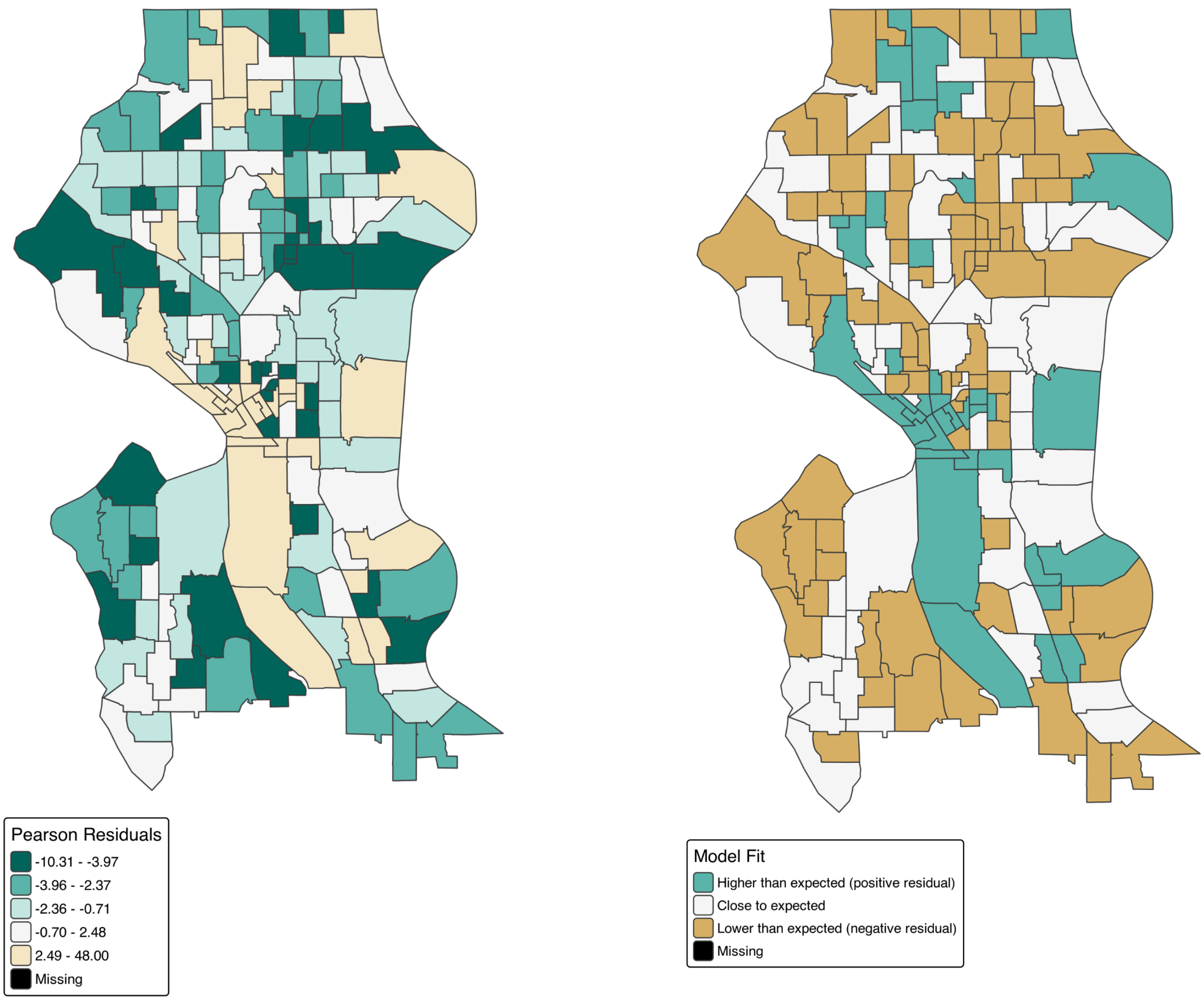
Incidence rate ratios (IRRs) and 95% confidence intervals (CIs) estimated from Poisson regression models with robust standard errors and a log population offset (n = 177 census tracts). Socioeconomic disadvantage is scaled per 0.1-unit increase in the index unless specified otherwise. Model 1 is unadjusted. Model 2 adjusts for log-transformed population density. Model 3 adjusts for neighborhood demographic composition, including percent male, percent aged 18-34, and percent BIPOC (excluding Asian). Model 4 additionally includes a spatially lagged UOF rate term as a sensitivity analysis to account for spatial dependence to Model 3. IRR > 1 indicates higher rates of police use of force associated with greater socioeconomic disadvantage.

Residual Spatial Autocorrelation

Pearson residuals from the fully adjusted Poisson model provided a means of assessing model fit across census tracts. Visual inspection of residual maps indicated spatial patterning, with clusters of tracts exhibiting similar residual values to one another. Global Moran's I for the residuals demonstrated statistically significant positive spatial autocorrelation ($I = 0.259$, $p < 0.001$).

Both continuous and categorized residual maps demonstrated that model fit varied geographically (Figure 3). The residual maps revealed clusters of census tracts with higher-than-expected and lower-than-expected UOF, indicating geographic variation in model fit across Seattle. The presence of spatial clustering in residuals indicates that model error is not randomly distributed across space, and that additional spatially structured factors not included in the model may contribute to variation in UOF rates.

Figure 3. Pearson Residuals from Fully Adjusted Poisson Model of Police Use of Force Across Seattle Census Tracts, 2020-2024



Pearson residuals from the fully adjusted Poisson regression model are shown to assess spatial patterns in model fit across census tracts. The left panel displays continuous residuals, representing the difference between observed and model-expected counts of police use of force (UOF), scaled by the model variance. The right panel displays categorized residuals using standard thresholds (< -2, -2 to 2, > 2) to highlight areas with relatively large deviations from model expectations. Positive residuals indicate tracts where observed UOF counts exceed model-expected values, while negative residuals indicate lower observed counts relative to expectations. Clustering of similar residual values across neighboring tracts suggests spatial patterning in model fit. Global Moran's I indicated significant positive spatial autocorrelation in residuals ($I = 0.259$, $p < 0.001$).

Post hoc Analysis

As a post hoc analysis, we added a spatially lagged UOF rate to the fully adjusted Poisson quasi-likelihood model to account for spatial dependence. The spatial lag term showed a positive association with UOF rates (IRR: 1.03, CI: 1.02, 1.04), indicating that UOF rates increased in census tracts surrounded by areas with higher UOF (Table 2). After inclusion of the spatial lag term, the association between socioeconomic disadvantage and UOF attenuated and no longer reached statistical significance (IRR: 1.04, 95% CI: 0.92, 1.17).

Although the estimated incidence rate ratio for the spatial lag term approached 1.00 when rounded at the 0.1-unit increase, this reflects the small unit measurement rather than a null effect. When scaled to a 10-unit increase in neighboring UOF rate, the association corresponded to an approximate 3% increase in UOF, indicating meaningful spatial clustering.

Discussion

This study examined the spatial distribution of police UOF across Seattle census tracts and assessed its association with neighborhood socioeconomic disadvantage (Figure 1). Findings from both spatial and regression analyses indicate that UOF exhibits meaningful geographic clustering, with higher rates concentrated in Central and South Seattle. Additionally, neighborhoods with greater socioeconomic disadvantage experienced substantially higher UOF rates, representing the primary disparity in this study. This association was evident in the unadjusted analysis and persisted, although somewhat attenuated, after accounting for population density and neighborhood demographic composition.

Positive spatial autocorrelation in UOF rates, identified by Moran’s I, showed that neighboring tracts tend to have similar levels of police UOF. This suggests that UOF patterns are influenced by broader neighborhood and spatial contexts. Local clustering analyses further demonstrated that these patterns are not evenly distributed across Seattle, but instead concentrated in central and southern neighborhoods, where high-high clusters and statistically significant hotspots occurred. These areas contain greater socioeconomic disadvantage, higher population density, and historical patterns of racial and economic segregation relative to many northern Seattle neighborhoods. They also include areas with dense transportation corridors, as well as commercial and nightlife activity, which may contribute to increased frequency of police-community interactions and opportunities for force encounters.

These findings align with a growing body of research suggesting that policing outcomes are spatially patterned and embedded within neighborhood-level conditions. Prior studies have demonstrated that policing practices, surveillance, and criminal legal system involvement are often concentrated within socioeconomically disadvantaged and racially marginalized communities. However, relatively few studies have applied spatial epidemiologic methods specifically to police UOF at the neighborhood level. By integrating hotspot analysis, local spatial clustering methods, and tract-level regression modeling, this study extends existing literature by demonstrating that UOF in Seattle exhibits meaningful spatial dependence and geographic clustering beyond what would be expected by random variation alone. Together, these findings support conceptualizing UOF as a place-based phenomenon shaped by neighborhood conditions.

Importantly, both the descriptive and regression analyses demonstrated a clear socioeconomic gradient in police UOF across Seattle census tracts. Neighborhoods with greater socioeconomic disadvantage experienced substantially higher UOF rates than less disadvantaged neighborhoods, and UOF rates increased progressively across quartiles of disadvantage. The presence of a gradient, and not an isolated threshold effect, is consistent with literature linking concentrated disadvantage to increased surveillance, enforcement intensity, and cumulative exposure to law enforcement (Hoekstra & Sloan, 2022; Theall et al., 2022; Kurlychek & Johnson, 2019).

Because the primary objective of this study was to examine disparities in UOF across neighborhoods with differing levels of socioeconomic disadvantage, the unadjusted model provides the most direct estimate of that relationship. Greater neighborhood socioeconomic disadvantage was associated with substantially higher rates of UOF, and this association remained largely unchanged after adjustment for population density and neighborhood demographic composition. The relative stability of estimates across model specifications suggests that differences in age structure, sex composition, and racial composition do not fully explain the observed disparities. Conceptually, these findings indicate that even among census tracts with similar demographic compositions, neighborhoods with greater socioeconomic disadvantage would still be expected to experience higher rates of UOF.

When the analysis incorporated spatial dependence, the association between socioeconomic disadvantage and UOF attenuated. This attenuation should not necessarily be interpreted as evidence that neighborhood disadvantage is unrelated to UOF. Rather, socioeconomic disadvantage is likely itself spatially patterned across Seattle, with clusters of concentrated disadvantage occurring in geographically contiguous areas. As a result, the spatial lag term may partially capture the same underlying geographic processes through which neighborhood disadvantage influences policing outcomes. From this perspective, the attenuation observed in the spatial model is consistent with the idea that socioeconomic disadvantage and UOF are embedded within shared spatial and structural contexts rather than representing independent processes.

Together, the findings suggest that neighborhood socioeconomic disadvantage operates within a broader geographic system in which structural disadvantage and policing practices are spatially co-located and potentially mutually reinforcing. Socioeconomic disadvantage and spatial dependence may therefore reflect interconnected features of the same underlying geographic processes. Shared policing districts and deployment strategies, spillover effects across tract boundaries, built environment characteristics that extend across neighborhoods, and broader historical and structural processes shaping patterns of segregation and disinvestment may all contribute to these patterns. Residual spatial autocorrelation remained after adjustment for measured covariates, suggesting that the analytic dataset did not capture important spatially patterned determinants of UOF. The persistence of residual clustering indicates that contextual factors operating across geographic space influence UOF beyond the characteristics of individual census tracts. The residual clustering and spatial lag findings also support the interpretation of UOF as a spatially structured phenomenon shaped by broader institutional and structural forces.

Strengths and Limitations

This study has several notable strengths. First, it integrates spatial epidemiologic methods with regression modeling to provide a more comprehensive understanding of UOF patterns. Second, the use of census tract-level data allows for examination of neighborhood-level structural factors while maintaining geographic specificity. Third, the application of multiple spatial techniques (Moran's I, LISA, and Gi*) provides consistent evidence of clustering and strengthens confidence in the observed spatial patterns.

Several limitations should be considered when interpreting these findings. First, the cross-sectional nature of the analysis limits causal inference; observed associations cannot establish temporal relationships between socioeconomic disadvantage and UOF. Second, UOF data are derived from police reports and may be subject to measurement error, reporting bias, and underreporting of force incidents (Lee et al., 2023). Third, the analysis is conducted at the census tract level, which may mask within-tract heterogeneity and is subject to the modifiable areal unit problem (MAUP), in which observed spatial patterns and statistical relationships may vary depending on the geographic scale or boundaries used for analysis.

Additionally, while specified covariates were included, unmeasured confounding and omitted spatial variables likely remain, as suggested by the residual spatial autocorrelation. The demographic covariates included in this analysis should also be interpreted as imperfect proxies for broader social and structural processes that are difficult to measure directly, including historical and contemporary patterns of racialized policing, residential segregation, differential police-community contact, and neighborhood disinvestment. Consequently, associations involving neighborhood demographic composition should not be interpreted as causal effects of those characteristics themselves, but rather as indicators of underlying structural conditions that may influence patterns of police UOF. The inability to successfully fit a negative binomial model due to convergence issues also limited the exploration of alternative model specifications for overdispersed count data. One additional limitation is that the spatial lag model represents a simplified approach to capturing spatial dependence, and more advanced spatial econometric models (e.g., spatial error, hierarchical spatial models) may better characterize these relationships.

Future Research

Future research should build on these findings by incorporating explicit spatial modeling approaches, such as spatial lag or spatial error models, to better account for spatial dependence.

Longitudinal analyses could also help clarify temporal relationships and assess changes in UOF patterns over time.

Further work is also needed to examine additional structural and contextual factors, including policing policies, resource allocation, neighborhood-level service availability, and historical patterns of segregation. Integrating qualitative or community-informed data may provide important insight into mechanisms underlying observed spatial patterns.

Finally, disaggregating UOF by level of force or incident type may help identify whether different forms of force are differentially associated with neighborhood conditions.

Public Health and Policy Implications

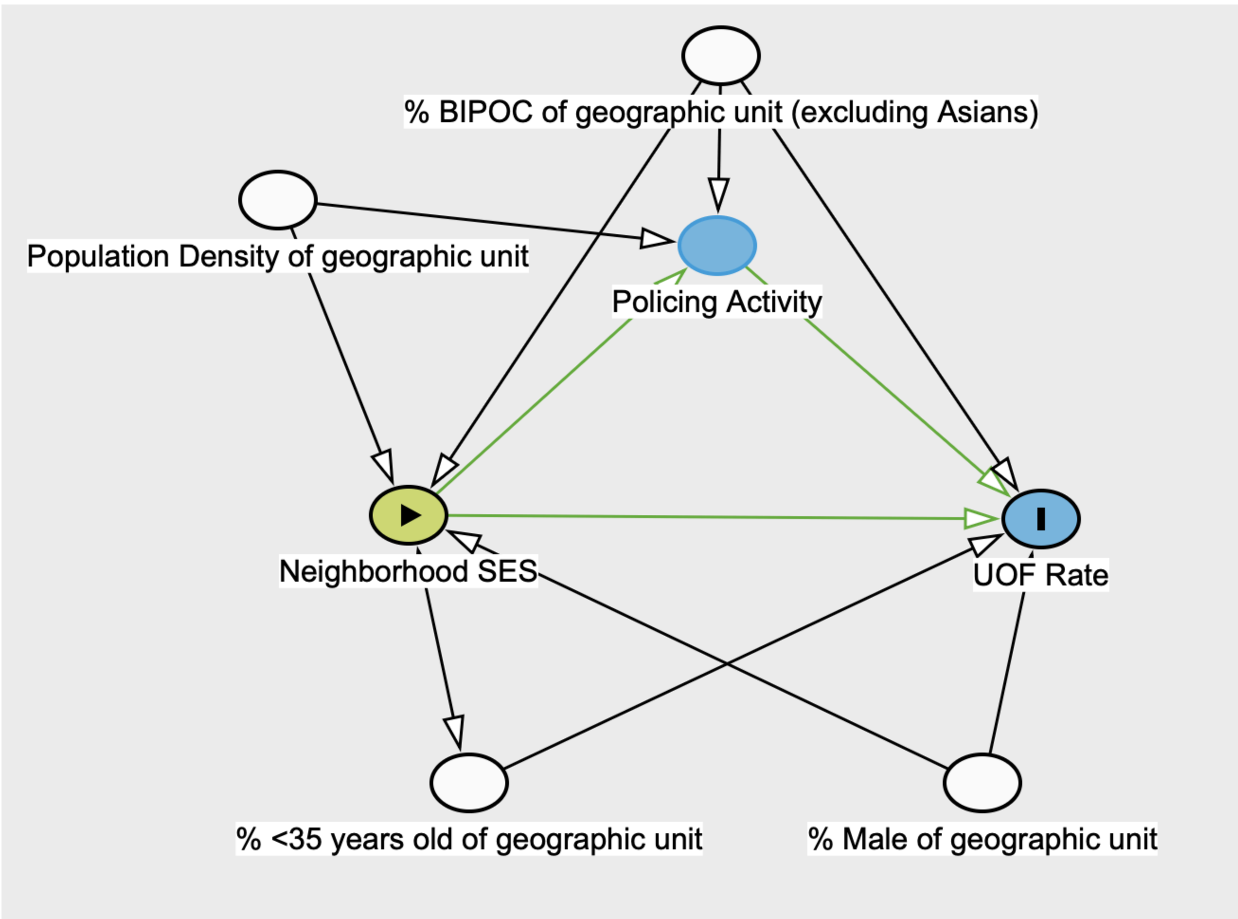
These findings also have important implications for public health research and practice. Public health approaches to violence prevention emphasize identifying and addressing upstream determinants of harm and understanding how exposures are distributed across populations. Within this framework, police UFO may be conceptualized as a population-level exposure with potential consequences for physical health, mental health, and community wellbeing. Although this study did not examine health outcomes directly, the observed spatial clustering of UOF suggests that exposure to police force is not randomly distributed across Seattle neighborhoods. Rather, higher levels of UOF were concentrated in communities experiencing greater socioeconomic disadvantage, indicating that potential exposure to policing-related harms may also be unequally distributed across geographic space. By identifying where UOF is concentrated, these findings provide an important foundation for future research examining the relationship between neighborhood-level exposure to police force and population health outcomes, as well as where public health interventions may be most needed.

Conclusion

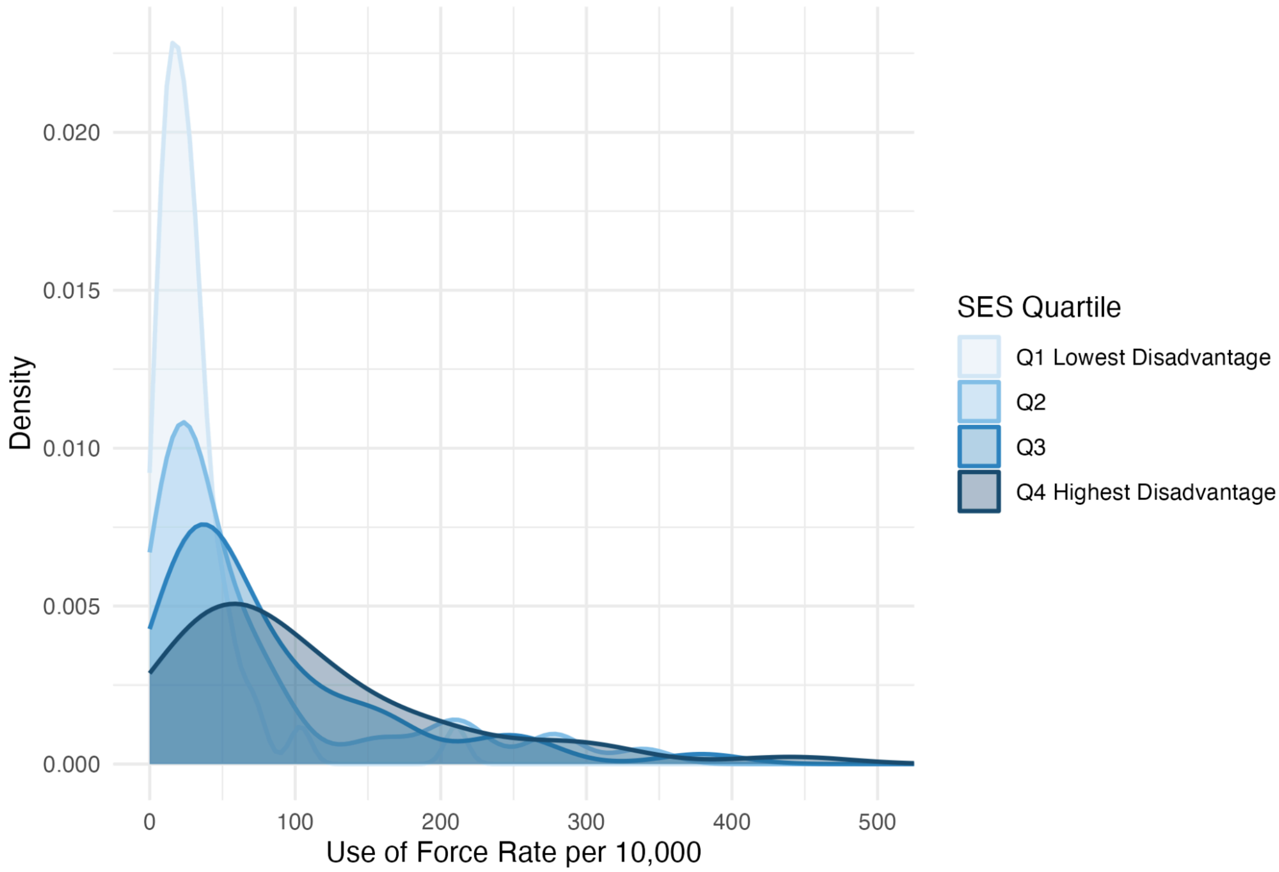
In conclusion, police UOF in Seattle is both spatially clustered and socially patterned, with higher rates concentrated in more socioeconomically disadvantaged neighborhoods. These findings underscore the importance of understanding UOF as a structural and place-based public health issue. Addressing these patterns will likely require interventions that extend beyond policing alone, incorporating cross-sector strategies to address underlying social and economic inequities and reduce harmful exposures at the population level.

Supplemental Figures

Supplemental Figure 1. Directed Acyclic Graph (DAG) of Neighborhood Socioeconomic Status and Neighborhood Use of Force (UOF) Rate



Supplemental Figure 2. Distribution of Use of Force Incidents by Socioeconomic Economic Disadvantage Quartile Across Seattle Census Tracts, 2020-2024



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